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Project Acronym: SMARTER

Project title: SteaM and gAs networks Revamping for the sTeElworks of the futuRe

Deliverable 6.1

Comprehensive overview of the project

Summary

1. Project Summary and ambitions

The present project aims at developing advanced methodologies and tools to support the revamping of gas and steam networks for improving energy efficiency and reducing CO_2 emissions as well as energy and management costs.

The ongoing pressure toward energy efficiency is expected to push steel companies toward an evolution of gas and steam networks in integrated steelworks through major modifications, such as addition of new junctions, new storage possibilities, and additional energy and gas sources. A more dynamic interaction with the energy market is also expected and an increased exploitation of renewable energy resources, which imply fluctuations in the energy costs and increased demand for flexibility of energy carriers' distribution and for rapid adaption to changes. Furthermore, the European steel sector is expected to undergo in the medium-long term a gradual transition toward C-lean processes and technologies, characterized by a novel and for many aspects not fully explored coexistence of traditional and innovative processes and production units, such as the Direct Reduced Iron (DRI) /Electric Arc Furnace (EAF) route including Natural Gas (NG) and hydrogen exploitation and/or auxiliary processes exploiting the energy and chemical contents of by-product gases. This gradual transition toward C-lean processes and technologies will indeed affect the gas and steam networks, and will imply a huge revamping of such networks, requiring a re-optimization of the whole network and the re-configuration of aggregates for a full exploitation of the advantages of the performed changes.

The system that will be developed within this project faces the above-mentioned challenge and will rely on computationally-efficient process models exploiting data-driven approaches, such as statistical, Machine Learning (ML)-based and hybrid ones, which will allow forecasting gas and steam productions and demands related to the different aggregates included in the networks and characterizing both standard and more innovative production routes. Moreover, physics-informed algorithms will be applied for modelling the networks topology. The proposed work is, therefore, considered incremental improvement for the relevant aggregate modelling and for the network modelling, as an approach of this extent has so far not been done in previous projects.

Advanced computationally efficient and license free optimization approaches will be applied, which are capable to achieve a suitable trade-off between precision and time-consumption, in order to meet the execution time constraints which allow improving the synchronization of connected processes within the networks. The final aim is to achieve an optimal match between gas and steam consumptions and demands, by thus reducing costs and emissions. Furthermore, distributed execution of optimization codes will be investigated as a solution to sustain the required computational burden at affordable costs, in order make the solution technically and economically viable for a large range of European companies. For the steel industry, SMARTER uses technologies such as ML and optimization for achieving a technical breakthrough progress with regard of usability and performance of such a system.

These novel models and optimizations tools will be used also to explore the behaviour of existing networks after the introduction of innovative processes to provide hints to be considered for optimizing energy management in the transition toward new configurations characterizing the steelworks of the future.

2. Detailed analysis of related previous and ongoing EU-funded projects

[P1] *RFRS-CT-2009-00032: Development of tools for reduction of energy demand and CO2 emissions within the iron and steel industry based on energy register, CO2 monitoring and waste heat power generation (ENCOP) 01/07/2009-31/12/2013.*

This project introduced a holistic approach to minimize the energy consumption and CO_2 emissions in integrated iron and steel plants. A set of software tools were developed to monitor and improve process performances and multi-objective optimization techniques were applied to improve off-gas distribution. Flowsheeting models were developed, which were adapted and translated into a fast Neural Networks-based version to be used in the optimization problem. However, the developed models were only static, the optimization was done only on a long time horizon and were not capable of facing short time events and rapid fluctuation of production or demand.

[P2] "*Optimization of the management of the process gases network within the integrated steelworks" (GASNET - RFSR-CT-2015-00029) 1/7/15-30/6/19*

This project aimed at improving the management of process off-gases in integrated steelworks through a proper distribution and an appropriate use of these gases. New dynamic Artificial Intelligence (AI)-based models of gas producers and consumers have been implemented including equipment for energy production. A hierarchical and decentralized optimization approach was also proposed in order to manage the different sub-networks on a short and medium term horizon, which exploits the forecasting provided by the models. A user-friendly monitoring system supporting operators in the management of the gas and steam network as well as the exploitation of the developed forecasting models was also developed. However, only a traditional integrated steelmaking route was considered and structural modifications of the network were investigated only through simulations. Both the models and the optimization approach developed in GASNET will be the starting point for the present project. With the focus on multi-target optimization, quick execution of approximation on distributed platforms and integration of new network elements such as a bridge pipeline, SMARTER yields a clear contrast and progress with respect to GASNET.

[P3] *FP6-2003: Ultra low CO2 steelmaking (ULCOS - NMP2-CT-2004-515660) 01/09/2005-31/08/2009*

This project investigated breakthrough technologies for alternative steel production route allowing to decrease CO_2 emissions. Among such technologies, NG-based pre-reduction reactors and hydrogen-based reduction using hydrogen were included.

[P4] *Integrated and intelligent upgrade of carbon sources through hydrogen addition for the steel industry (i3upgrade – GA 800659) 01/06/2018-30/11/2021.*

The project investigates the production of methane and methanol by exploiting the steelworks off-gases enriched with hydrogen. Experimentation of the behavior of synthesis reactors by using steelworks off-gases is ongoing. The best solution for green hydrogen production was evaluated through ad-hoc developed models in view of the implementation of the innovative synthesis processes in the integrated steelmaking route. Moreover, a dispatch controller for the correct management of the off-gas exploitation and hydrogen addition for methane and methanol production is under development by considering the reactors dynamics, the availability of hydrogen and off-gases and their quality, according to the integrated plant operating conditions and plans. A library of "site-level" models were developed together with models of methane and methanol production processes as well as of Polymer Electrolyte Membrane (PEM) electrolyser that were included in the dispatch controller. However, the project is focused mainly on the optimization of the use of the new synthesis processes (for methane and methanol production) and the overall impact of their introduction on the overall management of the gas and steam networks has not been deepened. The modelling approach and the know-how acquired during the project can be a starting point for the development of scenario analyses regarding future steelworks configurations (e.g. by including innovative processes).

[P5] *Hydrogen meeting future needs of low carbon manufacturing value chains (H2FUTURE, FCH-JU/H2020, 2017-2021)*

H2FUTURE is a flagship project for the generation of green hydrogen with renewable energy sources. A 6 MW PEM electrolyser plant was constructed and produces hydrogen at the site of the steel manufacturer voestalpine. The quasi-commercial operation will clarify that the PEM electrolyser is able both, to use timely power price opportunities and to attract extra revenues from grid services to improve price attractiveness. Experience in terms of technological know-how of low carbon hydrogen production and project results provide input to the models for hydrogen exploitation processes.

[P6] *LowCarbonFuture (RFCS, GA 800643, 2018-2020)*

This project summarized, evaluated and promoted research projects and knowledge dealing with CO_2 mitigation in the steel industry. Current pan-European research is focused on the 3 pathways Carbon Direct Avoidance (CDA), Process Integration (PI) and Carbon Capture, Storage and Usage (CCUS). The results of LowCarbonFuture stating research needs, requirements and boundary conditions for breakthrough technologies contribute to the model development and implementation of innovative steelmaking process concepts within the scope of the present project.

[P7] *Creation Of new value chain Relations through novel Approaches facilitating Long-term Industrial Symbiosis (CORALIS, CE-SPIRE-01-2020, 958337, 01.10.2020-30.09.2024)*

Industrial symbiosis (IS) has gain great attention in the last years due to its high potential for energy and resources savings. CORALIS has been designed as a demonstration project for the generation of real experiences on the deployment of IS solutions and the overcoming of the barriers faced by these initiatives. In total there are three demo cases and three follower cases.

One of the follower cases is located in the city of Linz, Austria, and focuses on the exchange of steelworks off-gases and green hydrogen between the voestalpine steel and Borealis Agrolinz Melamine. Different use cases will be analysed in terms of their technical and economic feasibility.

3. Relevant literature results

The European Steel Industry is in a massive change process. As an energy intensive industry, it is one of the most crucial industrial sectors to demonstrate the application of novel technologies to bring down CO_2 emissions. Changes mean revamping. In steel industry this also leads to careful and sound readjustments. One field of interest are the resource flows, more explicitly the off-gas, steam and energy networks. Balancing the different consumers and providers is a difficult task, as some resources originate from own furnace processes of the plants, others must be bought at the energy market. Ongoing revamping works change the structure of the networks and allow for a smarter, lean and effective capacity control. Yet, this must be calculated by an optimization system that in some way knows the demands in advance. The project SMARTER therefore covers three technological areas, whose current state-of-the-art is now discussed in more detail:

1) modelling processes and networks through machine learning (ML),
2) mixed-integer optimization
3) gas and steam network management.

3.1 Modelling processes and networks through ML, physics-informed ML and system identification

In the off-gas management optimization, the capability to forecast the off-gas and steam production (and related energy content) and demand of different processes, including energy transformation equipment is fundamental [1]. To this aim various physical- (for instance, based on process mechanism) and ML-based modelling techniques are applied in literature. Although the process-based methods show good accuracy, for instance, in forecasting off-gas generation [2, 3], they have some shortcomings in predicting future off-gas generation based on historical data or considering high non-linear process dynamics. These issues characterize also early data-driven techniques such as regression analysis models [2], Auto-Regressive (AR) and Moving Average (MA) models [3] as well as Auto-Regressive Moving Average (ARMA) models. More recent approaches exploit “intelligent forecasting” and ML plays a fundamental role, also considering the ongoing digitalization transition, wherever increasing volumes of process data are collected [4]. Advanced ML and Deep Learning (DL) methodologies are a clear turning point to achieve further improvements. These methodologies allow identifying and describing the process dynamics leading to improved accuracy and reduced computational burden compared to the standard modelling techniques. Noticeable examples are provided by Deep Echo State Neural Networks (ESN) [5-7] and Long Short-Term Memories (LSTM) [8]. A 30-min forecasting of the produced BFG flowrate was carried out by using input-output multilayer

Feed Forward Neural Network (FFNN) model [9], grey radial basis function NN [10], improved wavelet NN [11]. FFNN is used also in the case of prediction of thermal power required for the production of steam mass flow demand in auxiliary boilers as well as the electrical energy produced by the Blast Furnace Gas (BFG) expansion turbine [12]. Further works prove that ESN and Deep ESN are very effective for forecasting in medium time horizons (e.g. 2-hour) dynamic processes starting from process data being also computationally efficient. Some examples are related to the forecasting of BFG production in terms both of flowrate [7, 8][13, 14] and energy content [6][14], of Basic Oxygen Furnace Gas (BOFG) generation and steam production by recovering BOFG heat [15], BFG demand by hot blast stoves as well as steam and electricity demand by main steelworks users [1][7]. In [16] ESN are applied to forecast flowrate, CO, CO_2 and H_2 content of process off-gases in an integrated steelwork in a dispatch controller considering also their valorisation for the synthesis of methane and methanol.

In addition, the potential of combined or hybrid methods have been also studied and proved in different works for the prediction of BFG [17-22] and Coke Oven Gas (COG) generations [23]. However, all these modelling approaches are so far applied only to the traditional integrated steelmaking route.

Moreover, the network topology needs to be modelled as well in a reliable and computationally efficient way. In this context physics-informed algorithms provide interesting features and are used in an increasing number of applications. For instance, in [24] a network topology is reconstructed via multivariate Wiener filtering and consensus networks. In [25], an evolutionary optimization for physics-informed system identification is proposed, where the advantages of first-principle, white box models and ML black box models are combined to grey box models to estimate uncertainties. Such approaches are used to model ocean system electricity generation [26], proposing a physics-informed random forest. However, so far physics-informed algorithms have never been applied to model gas and steam networks in the steel field.

3.2 Mixed-Integer optimization and its application to gas and steam networks management

The problem of optimizing the distribution of Process Off-Gases (POGs) and in general the energy media exploitation within integrated steelworks has been addressed in different ways. Control and Supervision systems are the core of the strategy towards the energy optimization, and in turn, in general, they are characterized by a modelling of energy transformation which allows efficiently identifying the variables that can be manipulated to achieve optimal energy efficiency. Moreover, suitable optimization approaches are required, which are capable of handling variables of different nature (e.g. real and integer). Therefore, Mixed-Integer Linear Programming (MILP) has been often applied and sometimes coupled to predictive approaches for the control. For instance, a Mixed-Integer Model Predictive Controller (MPC) considering economic constraints and economic/environmental objectives is applied in [P2] for optimizing the energy conveyed by the off-gases in integrated steelworks [27]. Here MILP allows both describing with a good level of detail the dynamics of the energy exchange within gas, steam and electric networks and simplifying and lightening, the efforts for identification of optimal control strategies considering economic and environmental aspects. A hierarchical control system allows considering long term dynamics, for a control/prediction horizon greater than 1 day, and short-term dynamics of the order of 1 minute. In [28] a POG Dispatch Controller (DC) is implemented adopting an Economic Hybrid Model Predictive Control architecture [29], which solves in real-time an optimization problem formulated as a MILP for a receding horizon.

Similar approaches, although with simpler modelling and control, have been presented in the last 10 years in the literature. MILP has been exploited in [30-36] with the focus on the exploitation of POGs in the internal power plant. Some works also include the optimization of steam network as a thermal energy storage [32, 34] that allows to further increase the chances to optimize the energy distribution. In general, all the presented works try to optimize the POGs exploitation for a time horizon of maximum 90-120 minutes, while [36] shows a significant improvement achieving one day of time period.

In general, the mentioned results highlight two different aspects: firstly, in several steelworks the control of the POGs distribution for a time horizon greater than 1 hour is not a strict requirement, due to fast gasholder dynamics correlated to their very limited capacity and intensive consumption rates. Secondly, the involved processes are characterized by heavy nonlinear dynamics, difficult to model through standard methodologies, leading to short prediction horizon, and thus related control one. However, achieving longer prediction and considering a wider horizon enables improving the energy efficiency optimization through the formulation of strategic hints related to the scheduling of production processes. Improving the synchronization of connected processes can lead to a reduction of economic and environmental costs.

Computational burden might represent a limitation in the practical application of MILP in this context, especially if limited computational resources are available and/or fast reaction to unforeseen events is required. In [37] the execution speeds of different MILP solvers are studied and compared, proving the expected fact that commercial optimizers are by far quicker than the free and open source counterparts CBC or SCIP. [38] discusses novel ways of formulating the relaxation problem, introducing a decentral MPC to a steel production use case, that can be mapped with digital twins. Li et al. show in [39] the reformulation of the unit commitment problem to a 2-order moment relaxation that can be solved with semi-definite programming (SDP) and present methods on how the accuracy is affected and when exact solutions exists. The time horizon problem is well-known for MPC. Distributed execution of optimization codes is an urgent topic, as mixed-integer problems are as such difficult problems and require high computational capacity. For smart grid energy applications, [40] shows an exemplary work on how such a distribution can be applied to load scheduling. To ensure an orchestrated effort any distributed solver must coordinate sub-processes and subsystems, typically in an asynchronous way [41]. Co-optimization for water distribution and water-energy microsystems is presented in [42], where bivariate piecewise linear approximations is used to tackle the general non-linear programming problem. A mixed-integer solution for the multi-action planning problem is presented in [43], applying the technique to ecological threat prevention.

3.3 Gas and steam network management in the steelworks of the future

The steelworks of the future will include further greener energy carriers and processes. In this context, several research works are related to the Carbon Capture and Usage (CCU) or Carbon Capture and Storage (CCS) techniques that are often linked to the use of off-gases on a material bases for recovery of valuable compounds or for chemicals production. In addition, some others are related to the evaluation of the exploitation of hydrogen in substitution of fossil fuels or as energy storage. Some CCU scenario analyses are investigated in [44] and future challenges are considered in [45]. The exploitation of steelworks off-gases for chemicals production is investigated in [P4] to produce methane and methanol and in [46-52] both using experimentation and simulation and considering the enrichment of off-gases with green hydrogen [i.e. P4]. This last topic (i.e. green/sustainable hydrogen production) is fundamental if hydrogen is exploited in the steelmaking route; considerable amounts of hydrogen need to be produced, and thus technologies to produce/recover internally hydrogen directly by exploiting off-gases have been investigated [53-56]. Furthermore, the direct use of steelworks off-gases in the chemical industry as part of the industrial symbiosis will be investigated in [P7].

The best hydrogen production methods that can be coupled to green energy exploitation are investigated in [P4] and [P5] (for instance, PEM and Solid Oxide Electrolyser Cell - SOEC [57-59]) and the storage of hydrogen is discussed in [60] and [61]. The hydrogen transition is considered the future of the integrated steelmaking route. Different works investigate through modelling and simulation the effects of hydrogen injection in the Blast Furnace (BF), its exploitation for Direct Reduction (DR) [62-65] and the application of hydrogen-rich energy in iron ore sintering [66]. In addition, other possible evolutions of steelmaking route to reduce CO_2 emissions are investigated in [67-69] such as BF with gas recirculation or with carbon capture capability and a higher share of EAF-based steelmaking. The gradual introduction of innovative processes in the steelmaking route will affect the behaviour of off-gases and steam streams. Current network management procedures and supporting tools do not consider such future evolution.

4. Introduction and problem description

The steel industry is an Energy Intensive Industry (EII) and is therefore appointed as a major source of CO_2 and other emissions. Every regulation originated from European or local government hits the steel industry to a great extend due to the extraordinary market situation combined with the dramatically lower environmental requirements of the competitors form outside Europe. To be able to produce at competitive prices, the European Steel sector made and is making big efforts to improve energy efficiency by saving energy costs.

During the last years many research projects were processed focusing on energy efficiency and reduction of CO_2 emissions and these themes are indeed priorities in the agenda of the EU steel sector, being closely linked to the socio-economic and environmental sustainability of the steel production cycles. In 2015 the steel industry was responsible of 4% of CO_2 emissions in EU with a specific CO_2 emission average value of around 1300 kg CO_2/t_{CS} considering the 60%

produced by the BF/Basic Oxygen Furnace (BOF) route and the 40% by EAF routes. Comparing such data with the 1990, the combined specific emissions (BF/BOF+EAF) decreased by 14%, with a corresponding reduction of total emission is in the order of 28% due to lower production amounts. In this context, EU fixed a reduction in total emissions with respect to 1990 of 40% in 2030 and 80-95% in 2050 with reference to the C-neutrality concept that is the zero-net balance between emitted and released C into the atmosphere. These ambitious targets can be achieved, on one hand, by developing and deploying technologies allowing total reduction of CO_2 emissions stemming from EU steel ultimately leading to a climate-neutral steel industry. On one hand, CDA (for instance, the use of green hydrogen as reducing vector), which refers to the direct use of energy from renewable sources, optimal exploitation, use and valorisation of available energy sources and promotion of Circular Economy and Industrial Symbiosis, is one promising option to reach these goals. All the potential enablers providing energy management systems with improved flexibility and capability of self-adaptation and optimal reaction to variability in the production schedule and other unforeseen events will significantly contribute to a timely achievement of the above-stated targets.

The abstract approach of SMARTER is shown in Errore. L'origine riferimento non è stata trovata.. Steelworks transform, store, transmit and use various types of energy, where electricity, off- and by-product-gases and steam are among the most important ones. In order to comply with the goals of the Green Deal, steel producers constantly improve their networks and associated management practices in order to reduce the waste of resources and increase the overall efficiency. This is a huge revamping task at hand, for which they need the right tools to assist finding the optimum network and aggregate configurations. Such revamping, including new junctions, new storage possibilities, additional sources and innovative processes requires a re-optimization of the whole network and the re-configuration of aggregates, to fully exploit the impacts of these changes.

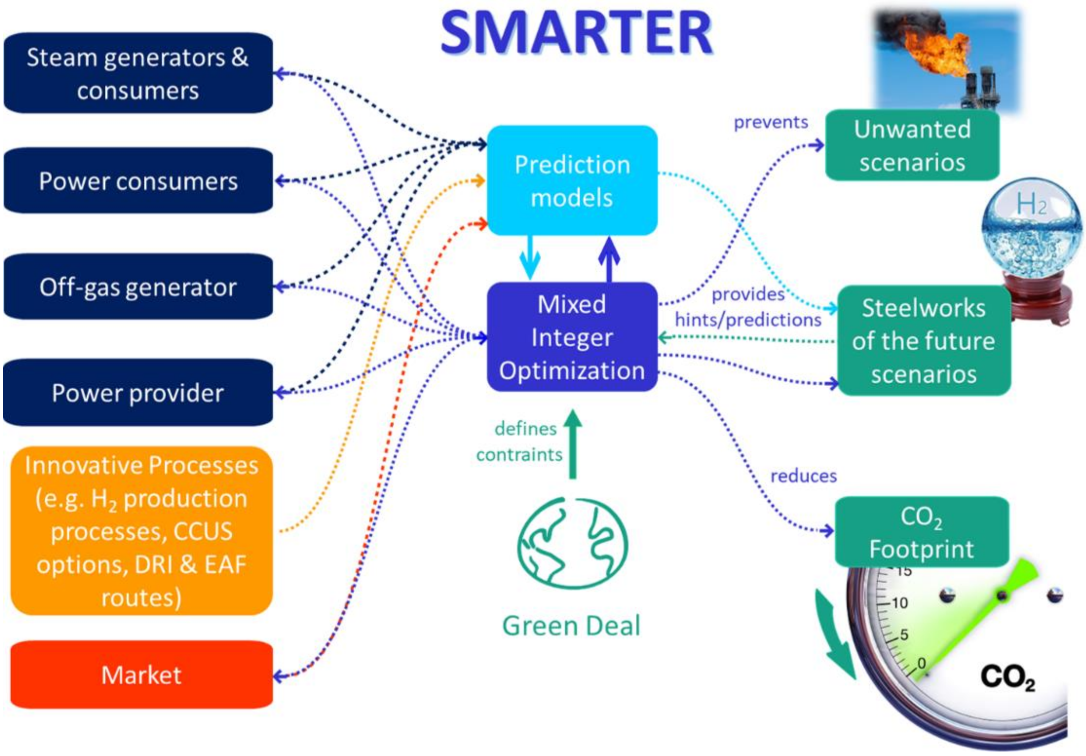

Figure 6.1-1. The SMARTER approach in a nutshell.

Large networks allow transfer of resources (off-gases, steam, electric energy) across the steel production processes and potential power plants. Especially for off- and by-product-gases as well as steam, it is desirable to use it wisely as they transport energy in form of heat and chemical energy. Reducing the waste of heat and optimizing its distribution consequently lead to a desirable improvement of the CO_2 footprint. The crucial point is here to save heat and to have off-gas and steam flows at the right aggregate, at the right time. Lack of harmonization between steam production and demand from the different sub-processes and utilities leads, for instance, to increased costs for NG purchase for satisfying peaks of demand and/or for maintenance for intermittent functioning of some of the available boilers. Sometimes, excess gas needs be burned via the flare(s), which is a highly undesired scenario. In this case, lower gas production or a different distribution can prevent this event.

The transition to carbon-lean steel making processes will not take place in one big step. It is assumed that these processes will gradually be integrated into existing plants. Therefore, gas- and steam networks will essentially be affected due to changing process conditions, gas compositions and amounts, etc. This must be taken into account for an overall evaluation of the benefits and effects of implementing innovative process units.

The optimization of off-, by-product-gas and steam distribution involves a complex series of tasks to perform the planning the network flows and to update it continuously:

a) It relies crucially on advanced models of the consumer processes, to simulate, predict and determine the outcome of a specific planning parameterisation.

b) Once in place, the models are used by an optimization strategy to evaluate the best configuration for a given optimization target such as CO_2 emission reduction, performance increase or homogenous machine utilization.

Networks of this type have been optimized in the past and the state-of-the-art analysis proposed in Sections 2 and 3 cites different projects that were committed to this problem. One of the biggest problems is hereby the fact, that some process routes can be represented by binary integer switches (on/off), which introduces integer values (0, 1, 2) into the optimization problem. These integer values are combined with the common floating-point values in the so-called Mixed-Integer (MI) problems. An outstanding feature of MI problems is a long computational time of the associated solution algorithm – the solver. In the network optimization, the solver is confronted with a series of process models to forecast different scenarios, which introduce their very own type of complexity. If the models show high computational efforts, their computation times exponentiate the solver evaluation.

Two problems arise from a control perspective: firstly, MPCs that use this type of MI algorithms yield a limited control and prediction horizons and second, the computational times may be higher than the actual process changes, allowing only a limited reaction. Especially, the second aspect means that the time until a result is found is often too long for quick control of the flows in the networks. Synchronizing changes in the processes with the optimization of off-gas, steam and power production is only possible by deploying computationally-efficient forecasting models. Data-driven models, including statistical, ML-based and hybrid ones, can provide a solution to this problem. Their development is receiving ever increasing attention in any industrial sector, including the steel one, as the ongoing digitalization process allows the acquisition of an ever increasing volume of data relevant to production and auxiliary processes.

The project will consider the following industrial use cases:

a) The re-vamping of junctions and pipelining at ArcelorMittal Bremen GmbH (ABG)
b) The “steelworks of the future” integrating novel C-lean production processes

4.1 Re-vamping of junctions and pipelining at ABG

The ABG plant in Bremen is already using its networks to balance the use of all its energy carriers. In a former project, the energy, off-gases and steam flows between the steelworks and its furnaces (producers), the forming processes (mainly consumers), and the power plant (producer) were studied and combined with optimizers. Currently, ABG and partner INGAVER, who operates the energy carrying networks, are revamping certain aspects of their networks and the units connected to the network (see an example in **Figure 6.1-2**). Their aim is to introduce new degrees of freedom in the distribution, which would improve flexibility.

Figure 6.1-2. Exemplary picture of a steam pipeline.

In the ideal optimum, only as much energy in form of gases, steam and electricity is provided as really needed by the production processes, requiring forecasting the demand as good as possible. To do this the SMARTER model library, which is developed jointly for all use cases by the project, will be used to simulate the plant of ABG and the network components of INGAVER. These forecasts can then be used for a mathematical optimizer to provide the best current setup for the network. Any impact of potential changes, improvements and further revamping activities can then be effectively predicted and optimized in advance.

Steel plants grow over time, with a heterogeneous fleet of equipment. Some parts are old, other parts are rather new. Not all parts show the same level of energy efficiency. Consequently, operators strive to reduce load and use of the inefficient aggregates as much as possible, potentially they even seek for ways to remove these systems completely. Therefore, networks are dynamic objects, as they undergo changes over time and any optimization must take such changes into account. In the use case of ABG a specific boiler unit was pointed out for future replacement or complete removal, which might be needed, but should be avoided as best as possible. This “changing network” problem has not yet been addressed before.

ABG and INGAVER have also identified highly unwanted scenarios for daily operation that a given optimizer should possibly prevent: a) burning gas through the flares, which is apparently the worst case scenario, as it represents energy waste and major CO_2 release and b) excessive overloads at their units, which would lead to wear and destruction of the equipment.

Resources such as NG and electric energy can be obtained from the energy market for a given, volatile and time varying price. They must be carefully balanced against the otherwise available resources to achieve an optimum exploitation. For the market, SMARTER will use stochastic modelling approaches and perturbation theory, in order to get ahead estimates for the evolution of the prices.

As can be seen from the following different aims for this use case

i) flexibility of distribution and adaption to changes,
ii) avoidance of inefficient units and preference of resource-saving units,
iii) overall availability of resources,
iv) reduction of waste
v) balancing of wear

the plant is confronted with a multi-objective optimization problem for which the developments of SMARTER will provide a solution.

4.2 The steelworks of the future

The by-product gases of voestalpine stahl (VAS) site Linz are already well distributed to be used as energy carrier for internal processes such as rolling mills, hot stoves or as input to the power plant (see **Figure 6.1-3**).

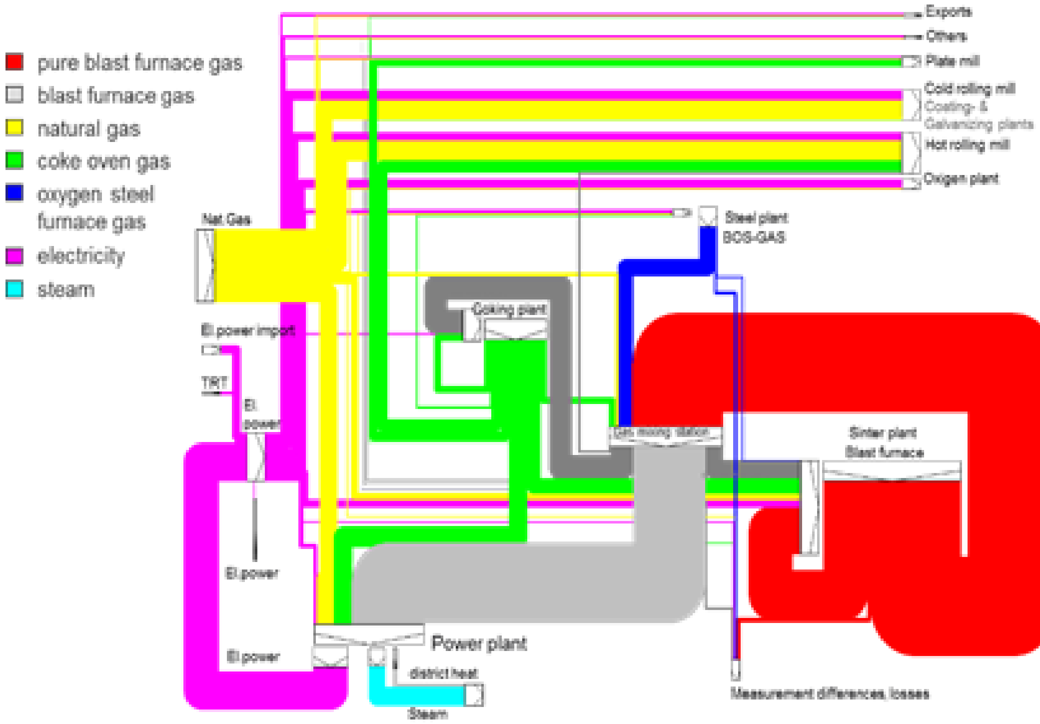

Figure 6.1-3. Energy flows of by-product gases at voestalpine Linz.

In the former project *i3upgrade* dynamic models for the utilization of carbon rich by-product gases for methane and methanol synthesis were developed which aimed at decreasing the overall CO_2 impact of an integrated steelworks. Reaching the goals of 80-95 % CO_2 reduction by 2050 requires further and profound measures for steelmaking processes. Implementing these new carbon-lean processes in an existing steelworks results in changing conditions for the network of using by-product gases. Replacing traditional process units such as a BF, Linz-Donawitz (LD)-converter or coking plant leads to a reduced availability of by-product gases, which somehow must be compensated by other renewable energy sources or an optimized distribution of the remaining gases.

Stationary process models developed within the scope of SMARTER enable the evaluation of these impacts on the overall energy and CO_2 balance which has not been addressed before. Therefore, a model library for innovative process steps (e.g. EAF, DR-unit based on NG and/or hydrogen, CCU options) including auxiliary units (e.g. renewable hydrogen production) will be set up in combination with a model of VAS`s existing gas network. In the use case of VAS different scenarios of how innovative process units can be implemented in the existing environment will be elaborated. Replacing parts of the existing BF/BOF route by an EAF will be a first step followed by the integration of a DR-process run on NG. For displaying a medium/long term view, the integration of hydrogen is indispensable for a substantial CO_2 reduction. Therefore, a hydrogen production unit (electrolyser) will be considered in the overall network model including a DR-process based on hydrogen as another evaluation scenario for the VAS use case. Furthermore, concepts for CCU-units will also be considered.

The evaluation scenarios for the VAS use case aim at:

i) best possible distribution of by-product gases;
ii) creating synergies for the utilization of existing and new gas streams;
iii) flexible integration of innovative process units in existing steelworks;
iv) maximized CO_2 reduction and energy efficiency.

5. Proposed technical solution including feasibility

Technically, there are three mayor elements that must be considered within the solution:

1) models for all relevant units / equipment parts are required to forecast the demand and production of consumers and producers,
2) models for the networks, their switch/junction configurations and pipelines and
3) a rigorous optimization/controller that takes all these models and calculates a solution for the flow configuration.

Moreover, the computation of the optimal solution should be fast enough to allow its implementation, therefore suitable approaches should be investigated to speed up the optimization procedure mainly by investigating into two (possibly complementary and not mutually exclusive directions):

1) reaching a trade-off between precision, accuracy and time-consumption;
2) distributing the computing

5.1 Forecast models for units/equipment

The project will develop a library of forecast models for gas and steam networks. It will start with re-using already available models whenever this is possible or re-adaption work is necessary. New models (if necessary) and model-adaptation will be done via machine learning (ML) techniques, exploiting and testing different methods such as Deep Echo-State Neural Networks (D-ESN) and Deep Liquid State Machines, Physics-Informed Neural Networks (PINN), Neural and Random Forests, but also traditional Feed-Forward Neural Networks. **Figure 6.1-4** shows illustrations of D-ESN and PINN.

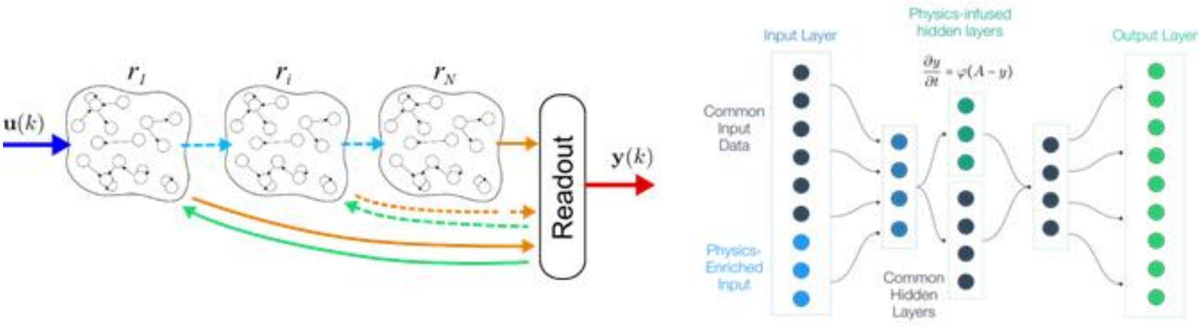

Figure 6.1-4. Schematic representation of (deep) ESN [6] (left) and physics-informed neural networks (right).

In case of innovative processes modelling, that are characterized by a few number of data with respect to standard processes, physical and/or semi-empirical methods will be also exploited as starting approaches for the development of static models; then after the generation of data by simulation, ML-based techniques will be applied for model improvement (e.g. in terms of dynamic).

5.2 Network models

Networks are practically modelled as graphs. Several of the existing network structures have been investigated and thoroughly documented either by the experts of ABG, INGAVER or within projects such as [P1] and [P2]. For SMARTER it is important to determine where the network is most vulnerable to inefficiency, where aggregates and network connections should be changed or improved or which is the best solution to connect innovative processes. This requires an alteration of the current state network model to the future plan or to some plan that is investigated by the plant. Using the SMARTER approach thus gives a tool to optimize the network even during the revamping design phase and after the revamping took place.

5.3 Optimization

As the different networks features are mostly represented by floating point quantities such as volume, pressure or voltages, they also essentially contain integer values like (0,1,2) which are caused for instance by on/off/modality states of aggregates (which furnace is used by the hot rolling mill, 1, 2 or 3? Is the flare active or not?), switches and junctions.

These integer quantities make the problem of finding the optimal solution difficult. For floating point variables, such kind of problem is conveniently covered by tools such as linear programming, quadratic programming or semi-definite programming. All these tools find a solution that would be enclosed by the four red lines in **Figure 6.1-5**. This is not the true optimum, as only the integer dots refer to the real states. The true solution is bounded by the blue lines. To find the optimum, one first solves for the (red) so-called relaxed solution between the red lines and, as soon as this solution is found, one iterates to an integer space for finding the integer optimum. This technique is called Mixed-Integer (MI) optimization. Free, open source and commercial solvers exist to solve these MI problems, normally requiring long runtimes (for the given problems between multiple minutes). Novel approaches take a closer look on the relaxed solution and then use approximations to find the optimum. However, these approximations are limited in their accuracy and precision.

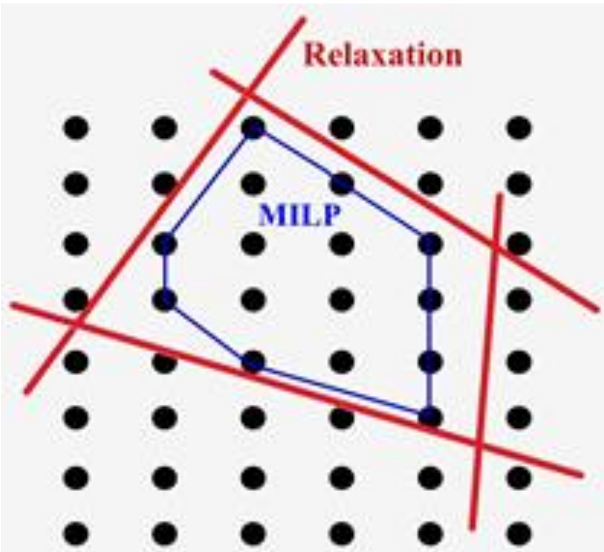

Figure 6.1-5. Discrete (integer) points (black), constraint space lines (red) and optimum solution (blue). Relaxation solution (space between the red lines), MI optimum (between blue lines).

5.4 Speeding up MI Optimizers: trade-off between precision, accuracy and time-consumption

A trade-off between precision and time-consumption arises that is at the centre of the presented project. Allowing a specific amount of uncertainty, the time for the calculation of the mixed-integer problem can be severely reduced and brought to a real-time execution capability.

5.5 Speeding up MI Optimizers: Distributed computation

Not only the approximation will increase execution speed, also the distribution of the algorithms to different process nodes can contribute to reducing execution time. Today, databases and according technology is designed for scale-up, where easy addition of hardware resources leads to an improvement of performance. To exploit such effects, the algorithmic designs for the aggregate models, the model of the network and the MI solver, must be designed in way that fosters distributed execution. This also requires an appropriate problem formulation, so that the utilization of the distributed computing approach can be fully exploited.

A project with this ambition would does not start on a fresh page, because former projects delivered important landmarks as a starting point for a fixed static situation: some models of the involved aggregates are available and will just have to be adapted to be used in the SMARTER approach. A first model of the networks is also ready but does not yet contain important revamping aspects.

6. Objectives of the project

As previously discussed, the importance of off-gases in the steelworks as energy carriers or as feedstock is highlighted by several literature works and maximizing their exploitation (internally or externally) is fundamental to improve the environmental (e.g. lower CO_2 emissions) and economic sustainability (e.g. improved reuse of valuable by-products). Similarly, the optimization of steam network management greatly affects energy efficiency and reduce costs associated to NG consumptions. The deployment of new energy carriers such as hydrogen or its exploitation in new environmental-friendly processes (e.g. DRI) is of utmost importance in order to pave the way to the transition toward the C-lean steel production which will characterize the steelworks of the future.

A transition phase of non-negligible duration is foreseen, where traditional process and alternative production routes will coexist and this will have strong impacts on the gas and steam networks. If not properly supported by adequate management tools and strategies, such coexistence can lead to relevant lack of efficiency, wastes of energy and reduction of the expected savings of CO_2 emissions compared to the potentials of the new processes. SMARTER aims at providing tools and means to support such transition by optimizing the management and the structure of the steam and gas networks in integrated steelworks both for the standard route and considering its future developments. Structural networks modifications are considered together with innovative processes and production units (e.g. DRI/EAF route including NG and hydrogen exploitation), which can affect the networks behaviour. To achieve such target, the following objectives are aimed:

- development and adaptation of models forecasting of gas, steam and power production and demands for all the involved processes, also through the exploitation of ML-based and hybrid modelling approaches allowing fast adaptation of the models to the changing features of the processes;
- analysis and revamping of gas and steam networks structure for more effective energy distribution and optimization;
- implementation of advanced energy optimization approach starting from heuristic approaches and later including novel real-time relaxation strategies;
- development of scenario analyses in order to assess how the implementation of innovative process steps in steelmaking chain can affect the networks behaviour and the overall energy management of the steelworks;
- implementation and field tests of the overall optimization concept and management tools on a distributed calculation platform;
- evaluation of environmental and economic impacts of optimized gas networks including innovative process units

7. List of Figures

8. List of symbols, indices, acronyms and abbreviations

Acronym	Name
ABG	ArcelorMittal Bremen GMBh
AI	Artificial Intelligence
AR	Auto-Regressive
ARMA	Auto-Regressive Moving Average
BF	Blast Furnace
BFG	Blast Furnace Gas
BOF	Basic Oxygen Furnace
BOFG	Basic Oxygen Furnace Gas
CCS	Carbon Capture and Storage
CCU	Carbon Capture and Usage
CCUS	Carbon Capture, Storage and Usage
CDA	Carbon Direct Avoidance
COG	Coke Oven Gas
D-ESN	Deep Echo-State Neural Networks
DL	Deep Learning
DR	Direct Reduction
DRI	Direct Reduced Iron
EAF	Electric Arc Furnace
ESN	Echo State Neural Networks
FFNN	Feed Forward Neural Network
LD	Linz-Donawitz
LSTM	Long Short-Term Memories
MA	Moving Average
MI	Mixed-Integer
MILP	Mixed-Integer Linear Programming
ML	Machine Learning
MPC	Model Predictive Control
NG	Natural Gas
PEM	Polymer Electrolyte Membrane
PI	Process Integration
PINN	Physics-Informed Neural Networks
POG	Process Off-Gas
SOEC	Solid Oxide Electrolyser Cell
VAS	voestalpine stahl

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